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# A quantum-driven multi-stage framework integrating variational entanglement, reinforcement learning, and federated explainability for climate-resilient farming

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**The increasing constraints of climate change and data privacy necessitate high-efficiency, sustainable agriculture, which is causing a shift in the paradigm of Agro-informatics. Most classical agricultural models fail to capture genotype, soil chemistry, and climate dynamics connections. Latent interactions, essential to intelligent agricultural treatments and explainability, are lost in many data processing pipelines that use linear dimensionality reduction or black-box learning. This paper presents a quantum computing architecture for a revolutionary agricultural application, utilizing quantum encoding, topological learning, reinforcement optimization, federated intelligence, and explainability to highlight the importance of this vital field. In Quantum Variational Crop–Soil Entanglement Encoding, crop-soil interaction datasets are encoded into quantum state vectors using variational circuits, preserving high-order entanglement properties (fidelity > 0.96, entropy ~ 0.9). Quantum-guided agri-topological dynamics mapping transforms encoded states into permanent topological maps using a hybrid quantum–classical Topological Data Analysis to track climate-induced agri-system dynamics (r = 0.84 with the yield index). Field-level decisions using Quantum Reinforcement Learning for Precision Intervention policy mappings to relate topological states to interventions produce 16.2% normalized yield. Quantum Federated Learning for Distributed Farm Intelligence uses privacy-preserving, encrypted quantum policy gradients to enable learning across farms in varied locations, lowering communication by 42% and improving accuracy by 9.3%. Quantum Explainability through Entropic Intervention Attribution generates causal graphs of yield drivers with 89% confidence intervals using entropy-based attributions. This integrated framework enhances the knowledge preservation, policy accuracy, expandability, and trust of agricultural Artificial Intelligence systems, enabling quantum-accelerated, information-based, future-ready farming decision support systems.**

**Keywords** Quantum computing, Smart agriculture, Variational entanglement, Topological data analysis, Federated learning, Distributed farm intelligence, Quantum encoding, Crop soil interaction

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**Abbreviations**

| | |
|---|---|
| 3D | Three dimensional |
| AI | Artificial intelligence |
| APSIM | Agricultural production systems simulator |
| CNN | Convolutional neural network |
| COâ | Carbon dioxide |
| CSA | Climate-smart agriculture |
| DL | Deep Learning |
| DSSAT | Decision support system for agrotechnology transfer |
| GPS | Global positioning system |
| IoT | Internet of things |
| LSTM | Long short-term memory |
| ML | Machine learning |
| N/A | Not applicable |
| NISQ | Noisy intermediate-scale quantum |
| NLP | Natural language processing |
| NPK | Nitrogen, phosphorus, and potassium |
| PCA | Principal component analysis |
| QE-EIA | Quantum explainability through entropic intervention attribution |
| QFL-DFI | Quantum federated learning for distributed farm intelligence |
| QG-ATDM | Quantum guided agri-topological dynamics mapping |
| QRL-PI | Quantum reinforcement learning for precision intervention |
| QV-CSEE | Quantum variational crop-soil entanglement encoding |
| RNN | Recurrent neural network |
| SAM | Social accounting matrix |
| S-box | Substitution box (cryptographic function) |
| SDG | Sustainable development goals |
| TDA | Topological data analysis |
| TS | Time series |
| WSN | Wireless sensor network |
| XAI | Explainable artificial intelligence |

Convergence between quantum computing and smart agriculture can lead to something fundamentally transformative in addressing modern challenges to food production, environmental sustainability, and resilience to climate change. Global agricultural systems face increasingly complex problems due to the growing geospatial diversity, climate variation, and interactions among soil, plants, and microbes. Therefore, a clear need arises for data-driven decision-making frameworks that can model non-linear, high-dimensional, and temporally dynamic relationships. Due to limitations in representational fidelity, data compression, and the inability to preserve higher-order feature interactions, traditional machine learning (ML) and statistical methods[1–3] often fail to capture these phenomena. The expanded dimension of Agri-data raises further concerns over computational cost, interpretability, and data privacy, increasing the need for a new class of intelligent systems. Quantum computing, by its nature, encompasses superposition, entanglement, and high-dimensional Hilbert spaces, promising to be the ideal computational substrate for encoding and processing complex interactions in agroecology. Early applications of quantum computing in agronomic problems have been optimised for specific needs, such as crop scheduling and supply chain logistics; this research expands the integration frontier by embedding quantum-native intelligence through the entire agricultural data processing pipeline (feature encoding, policy learning, explainability). This is paramount since agricultural phenomena are mostly not linearly separable or temporally static, requiring an entirely different approach than classical feature extraction and black-box predictive modelling paradigms to capture them effectively.

In this context, the research proposes a quantum framework that integrates various quantum algorithms systematically to target specific pain points in agricultural data science. Starting from the quantum variational encoding of crop soil interactions, topological mapping of climate-induced dynamics[4–6], and proceeding through the reinforcement learning of adaptive interventions, federated and interpretable quantum policies, each method constructs an essential building block for scalable and intelligent agricultural systems. By its nature, quantum Topological Data Analysis (TDA) connects time and geography to observe persistent spatial–temporal features, while ensuring data privacy and the richness of learned models through the integration of federated quantum learning. The framework also enhances decision-making and improves transparency and trust among stakeholders by directly embedding explainability into the quantum pipeline through entropy-based attribution. The paper lays the groundwork for a foundational framework on quantum-enhanced smart agriculture, extending beyond isolated applications and multi-stage building pipelines. In its open-ended approach, the quantum-native system aims to provide hyper-resolution decision support in precision agriculture, a distributed platform for intelligence sharing among farms, and offer scientifically interpretable insights into the causal mechanisms underlying agricultural outcomes. Through a rigorous design, simulation, and evaluation of each method, the work aims to demonstrate that quantum computing is not just a theoretical novelty but a practical enabler of next-generation Agri-intelligence systems.

## Motivation & contribution

The driving motivation behind this research stems from the limitations of classical AI techniques, which cannot effectively manage modern agricultural data due to its multimodal, spatiotemporal, and high-dimensional complexity. Traditional data compression methods, such as Principal Component Analysis (PCA) and autoencoders, often fail to retain non-linear interdependencies between soil chemistry and crop genotype, as well as many environmental variables and historical interventions. Similarly, classical approaches to reinforcement learning are executed over handcrafted or heavily simplified representations of the state space, wherein topologies intrinsic to the Agri-ecological systems that determine yield outcomes under varying conditions are also ignored. Modern superconducting and trapped Ion computers have 20 to 100 qubits, microsecond coherence times, and gate fidelities below 99.9%. The Noisy Intermediate-Scale Quantum (NISQ) age of quantum technology hampers complex agricultural analytics. Physical constraints limit live computation circuit depth and iterative optimization. Qubit crosstalk and delayed calibration drift can affect high-fidelity state preparation for the Quantum Variational Crop–Soil Entanglement Encoding (QV-CSEE) module and topological dynamics mapping sets. Small quantum circuits with 14 layers and 20 active qubits are designed for agricultural applications. The architecture anticipates ongoing developments in qubit coherence, error correction, and interconnection for next-generation quantum devices and deployments. The quantum agriculture framework shall scale from experimental plots to regional or national farming networks as hardware advances deeper circuits, larger qubit registers, and wider geographic deployments. Centralised learning models also create critical issues in terms of scalability, privacy, and generalisation when deployed across distributed, heterogeneous farms. With this chemistry, there is a great need for a more expressive, safer, and context-based framework that leverages the theoretical advantages of quantum computation for modelling and optimisation of agricultural systems.

To fill that gap, the research proposed a comprehensive framework comprised of five interrelated tools, each addressing a unique challenge along the agricultural modelling pipeline. The QV-CSEE solution will preserve the entanglement-rich latent features of soil crop interactions through variational quantum circuits, enabling superior information compression. The Quantum Guided Agri-Topological Dynamics Mapping (QG-ATDM) solution employs a quantum–classical TDA pipeline to map dynamic topological changes in Agri-systems in response to simultaneous changes in climate and spatial inputs. Quantum Reinforcement Learning for Precision Intervention (QRL-PI) further learns high-fidelity intervention strategies directly from these topological states, outperforming classical RL in precision and adaptability. Quantum Federated Learning for Distributed Farm Intelligence (QFL-DFI) utilises QFL and encrypted gradient sharing to address the challenge of distribution-based scalability and privacy. Finally, Quantum Explainability through Entropic Intervention Attribution (QE-EIA) implements an entropic attribution mechanism, which enables the tracing of causal factors to their decision outcomes, thereby embedding interpretability into the quantum policy framework. These methods, when combined, form a unified architecture that advances the technical frontier in quantum computing for agriculture, yielding meaningful practical outcomes such as resource optimisation, sustainability, and stakeholder trust.

## Review of existing models used for smart farming crop analysis

This journey begins with works like those of Ibrahim et al.[1], which used AI-IoT fusion to facilitate the early detection of diseases in crops and optimise treatment using a pivot system. Abdelhamid et al.[2] further advanced this concept by introducing solar-powered smart irrigation, branding this innovation as sustainable energy sourcing in precision water management. Mitra et al.[3] presented a comprehensive review that highlighted the core building blocks of Climate-Smart Agriculture (CSA), while also exposing the interoperability and system integration requirements. These gaps were narrowed by Balasubramanian et al.[4], who introduced a power-aware management system using RNN-LSTM networks, improving dynamic resource allocations. Bhandarkar et al.[5] enhanced user accessibility through a voice-based intelligent interface for farmers, thus encapsulating the whole set of inclusivity in Agri-tech systems. Thilakarathne et al.[6] attempted to address an overtly neglected topic, cybersecurity, proposing a threat intelligence platform for evaluating vulnerabilities within agriculture-related IoT installations. At the same time, dense CNN architectures applied in recognising crop classification were expanded by Sivaraj et al.[7], which established improved hypothesis accuracy in heterogeneous data environments. Tey et al.[8] further conducted a meta-layer analysis through patent network mapping to examine technology trends in innovation diffusion related to CSA. Vaithianathan et al.[9] thus carried these into a new convergence frontier by linking food quality, healthcare security, and cloud-based ML. Nawaz et al.[10] discussed the limitations presented in such environments, particularly regarding resource scarcity, and called for scalable AI solutions relevant to low-infrastructure contexts. These structural disadvantages in gender and access were examined by Nchanji et al.[11]. Fattouch et al.[12] proposed a business process-aware modelling approach, anchoring smart agriculture within enterprise process frameworks. Groundwater governance and the regional implementation of CSA were discussed by Roy et al.[13], who customised adaptive practices according to local hydrological realities. Christmann et al.[14] extended this concept to urban applications, portraying smart urban agriculture as a potential intervention in highly populated ecosystems. Manoj et al.[15] then utilised blockchain-supported federated learning to ensure trusted and decentralised model training among farms, particularly addressing concerns related to privacy and model generalisation. Islam et al.[16] analysed the poverty impact of CSA, showing a multidimensional upliftment of communities in coastal Bangladesh. Tambol et al.[17] contextualised the adoption of CSA, while Srinivasan et al.[18] addressed energy efficiency using hierarchical clustering for data fusion in sensor networks. Boufares et al.[19] went a step further in sensorized architecture by embedding 3D object recognition, thus enabling mobile distributed systems. These hardware and network improvements were then integrated into actual operations within an innovative greenhouse framework under the Agriculture 4.0 Initiative.

Cartolano et al.[21] emphasize explainability in AI by assessing XAI models with applications in agricultural contexts, thereby ensuring transparency and stakeholder trust. The work by Nawaz et al.[22], however, highlighted the importance of AI-IoT integration in building climate resilience. Maity et al.[23] have introduced the robust Smart Tech-Agri devices for field monitoring, merging device engineering with AI-driven analytics. Along the same line, Davila et al.[24] would map CSA to civil-society initiatives and note the grassroots contributions to agricultural adaptations, introducing a sociopolitical angle. With AI-based diagnostics, Tej et al.[25] have taken the first step in developing a plant disease detection system in Tunisia, moving forward with localised training at the model level. Ma et al.[26] and Ajatasatru et al.[27] have also provided this opportunity through a Social Accounting Matrix (SAM) model, which quantifies the macroeconomic effects. The meta-review examined CSA extension services in terms of adoption determinants and stakeholder collaborations, as per Thottadi and Singh[28]. Research by Atta-Aidoo et al.[29] probed into resource thresholds critical for CSA implementation in Ghana, identifying cost as a major constraining factor. Zhou et al.[30] proposed a hybrid image protection model based on the principles of annealing and chaos theory for securing visual data in agriculture, thereby addressing the concern of cybersecurity in digital imaging. The works of Oteng et al.[31] and Midjangninou et al.[32] evaluated the improvements in food security among cassava farmers in Benin under CSA programs by assessing gains in income stability measures. Karthickmanoj et al.[33] demonstrated the early detection of disease using IoT-based leaf imaging, which automates anomaly classification at early stages. Sharma et al.[34] submitted the S2AM model, which embodies sustainable crop protection using deep learning (DL), for evaluation with computational complexity and ecological indicators. Dhanke et al.[35] benchmarked DL models across various climatic zones, demonstrating that tuning for specific weather conditions can significantly enhance forecasting accuracy. Villalba et al.[36] analysed CSA credit frameworks in the Indo-Gangetic plains to cover CSA financing gaps. Singh et al.[37] introduced a composite indicator framework for tracking the effectiveness of CSA and a policy tool that summarises results against thematic indicators. Applications of nano-bonechar in agriculture were explored by Imtiaz et al.[38]. This demonstrates a redesign towards nano-enabled soil conditioning. Fister et al.[39] presented variants of time series association rule mining for sequential decision-making, considering the temporal evolution of agricultural patterns. Finally, Ali et al.[40] concluded with a comprehensive treatise on ML and DL models in the detection of drought stress, solidifying AI's role within adaptive response strategies.

Table 1 presents a summary of the literature synthesis, which includes major references, their methodologies, the primary objective of the research, the main findings, and the limitations reported by these researchers. It notes that most current methods rely on linear models or black box learning, which may tend to overlook high-order interactions when defining accurate agricultural interventions. The table highlights the discontinuities, including poor data fidelity, limited interpretability, and the scarcity of privacy-preserving frameworks. The given synthesis has unequivocally defined the necessity of further models, such as a quantum-integrated framework, which can meet these requirements by providing robust information preservation, higher-quality decisions, and explainability in various agricultural contexts.

| Ref | Method | Main objectives | Findings | Limitations |
|---|---|---|---|---|
| [1, 10, 23, 33] | AI–IoT smart systems | Plant disease detection, field monitoring, and lightweight deployment in resource-constrained areas | Achieved early disease recognition and precision monitoring through AI IoT integration | Scalability in large farms and false positive rates are not fully addressed |
| 2,14,20 | Smart urban/Controlled agriculture | Sustainable irrigation, vertical farming, and greenhouse integration | Reduced energy use and validated urban frameworks with Industry 4.0 integration | Limited rural adaptability and incomplete cost evaluation |
| 3,28 | Systematic/ Comprehensive reviews | Survey of CSA technologies, drivers, and service synergies | Mapped AI IoT applications and CSA adoption drivers | Mostly conceptual, lacking causal quantification or experimental validation |
| [4, 18, 19] | Edge & Sensor fusion (RNN-LSTM, clustering, 3D sensors) | Energy efficiency, mobility, and adaptive decision-making | Improved energy efficiency, dynamic responses, and object recognition | High computational load and resource-intensive sensors |
| 5,21 | Human-centric interfaces (Voice, XAI) | Farmer accessibility and trust in AI | Improved interaction and transparency | Dialect limitations and weak model generalizability |
| 6,30 | Cybersecurity (CTI, Secure Imaging) | Threat detection and visual data protection | Established risk profiling and secure data encoding | No real-time mitigation and computational overheads |
| [7, 25, 34, 35, 40] | Deep learning models (CNN, RNN, hybrid) | Crop identification, disease detection, and yield forecasting | Increased accuracy, improved forecasts under climate variability | Hardware dependency, dataset bias, and limited climate re-simulation |
| 8 | Patent network analysis | Tracking CSA technology evolution | Identified clusters and innovation gaps | No validation of real-world impact |
| 9 | Cloud ML quality monitoring | Crop health data integration with healthcare | Linked cloud analytics to food quality | Latency issues in real-time scenarios |
| [11, 16, 17, 24, 26, 27, 29, 31, 32, 36, 37] | socioeconomic & policy Studies (Gender, poverty, adoption, financing) | Assessing CSA access, adoption drivers, and economic impact | Demonstrated CSA's role in poverty reduction, food security, and adoption determinants | Geographic or sectoral constraints, limited scalability, and a lack of longitudinal analysis |
| 12 | Business process modelling | Formal verification of Agri-processes | Introduced structured CSA process workflows | Simulation-only validation |
| 13,38 | Water & soil studies (Groundwater, nano-amendments) | Aligning CSA with water-smart practices and soil quality | Region-specific water-smart strategies. nano-bonechar showed potential soil benefits | Absence of predictive modelling and early-stage trials |
| 15,22 | Blockchain and federated learning | Privacy-preserving distributed CSA models | Secured model training with enhanced scalability under climate stress | High computational and communication overhead |
| 39 | Time-series rule mining | Sequential agricultural trend analysis | Captured evolving Agri-system patterns | Limited interpretability |

**Table 1**. Literature synthesis detailing methodologies, research objectives, key results, and limitations.

## Gaps analysis of existing models

It has been proven by current literature that classical techniques of ML used along with IoT sensors substantially improve the agricultural analytics, whereas federated and blockchain-supported frameworks enhance privacy and facilitate distributed learning. DNN and RNN have been applied to crop yield prediction and disease detection, and agricultural development models like DSSAT and APSIM are still valuable for long-term planning direction. Nevertheless, these methods primarily rely on linear or shallow non-linear projections, which can only weakly represent highly intricate interactions between soil, crop, and climatic variables, thus restricting accuracy, flexibility, and interpretability in practical decisions. Recent TDA and graph-based learning methods address spatial complexity; however, most of these methods use static homology or single-season representations. Shapley-value or saliency hypotheses explain local sensitivities but rarely agricultural consequences. Private-preserving DL reduces centralization but demands high communication bandwidth, hampering resource-constrained farms. Gaps inspired the quantum-driven framework. Conventional compression cannot capture high-order entanglement in soil chemistry, plant physiology, and climate dynamics as effectively as quantum variational encoding. QRL examines intervention methods in a richer state space, thereby accelerating convergence compared to classical agents. Finally, entropy-based causal graphs match emerging agricultural AI trust norms with globally consistent, transparent attributions. The suggested design advances the state of the art beyond incremental gains from existing approaches by addressing complexity, interpretability, and privacy.

## Proposed model design analysis

The integrated quantum-smart agriculture framework developed in this research is structured as a layered computational architecture that transforms raw multimodal agricultural data into interpretable quantum decision policies for the process. First, as shown in Fig. 1, each layer in the structure performs a distinct quantum information processing function, namely, encoding, topology extraction, learning, aggregation, and attribution, which aims to preserve, model, and operationalise the complex dependencies governing the resulting agroecological outcomes. The integration across layers is achieved by the contextual mapping of input modalities to quantum circuit representations, followed by the use of quantum–classical hybrid models that adaptively tune operations using optimisation criteria grounded in entanglement metrics, topological persistence, and policy fidelity sets. The first encoding layer, QV-CSEE, maps soil crop datasets into a quantum state using a parameterised variational quantum circuit in process. Given a classical dataset $D=\{(\vec{x}_i, \vec{y}_i)\}$, where $\vec{x}_i$ represents soil chemical features and $\vec{y}_i$ corresponds to crop genotype phenotypes, the encoding operation aims to construct a joint quantum state $|\Psi(\theta)\rangle$ that preserves latent entanglements.

In Fig. 1, the encoded quantum state vectors are transmitted into the QG-ATDM module, where persistent homology produces topological signatures after the quantum states, subjected to changes in climate, are processed in the operation sets. Thus, serving as entropy-normalised weights to prioritise persistent features.

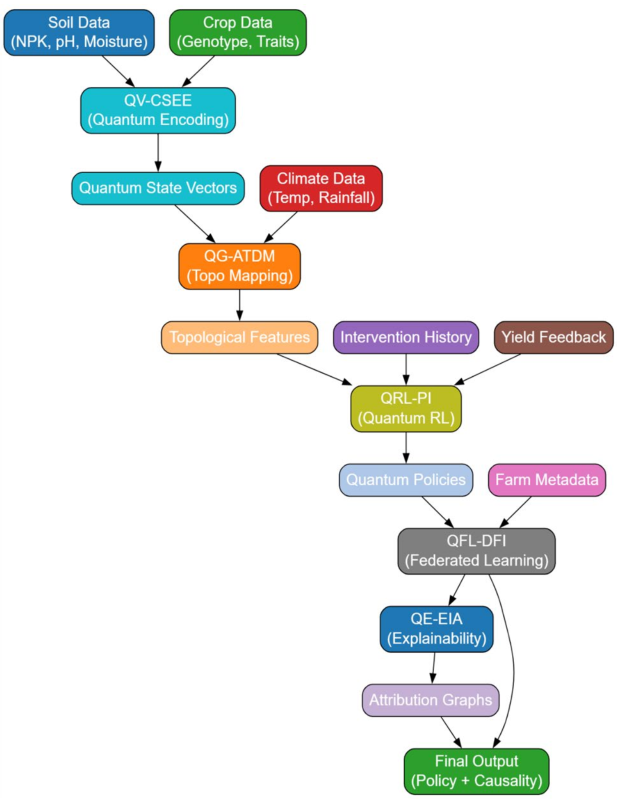


**Fig. 1**. Model architecture of the proposed analysis process.

The parameterised ansatz U(θ) is optimised to minimise the fidelity loss function via Eq. 1,

$$Lfidelity = 1 - |\langle \Psi true\, | U\,(\theta) |\, 0 \rangle|^2 \tag{1}$$

where, |Ψtrue⟩ is an idealised reference state capturing true interactions in process. To compress these into low-dimensional latent representations ρenc, the Von Neumann entropy is regularised during training via Eq. 2,

$$S\,(\rho enc) = -Tr\,(\rho enclog\rho enc) \tag{2}$$

In this way, it will ensure that the quantum state maintains the non-trivial entanglement required for downstream inference sets (range available: S in [0.88, 0.93]) throughout the process. Represent Variable time datasets as Q(t) and represent $F_r(Q(t))$ as the Vietoris Rips complex at a filtration radius 'r', thus representing the process in question sets.

The persistence of the topological feature is captured by the Betti numbers $\beta_k(t)$, while stability is assessed using the bottleneck distance, as shown in Eq. 3.

$$dB\left(D^1, D^2\right) = inf\gamma sup\left\{x \in D^1\right\} ||x - \gamma\,(x)|| \tag{3}$$

where $D_1$ and $D_2$ are persistence diagrams at different timestamp sets. These topological features are integrated using an entropy-weighted temporal persistence function, represented via Eqs. 4 and 5,

$$P\,(t) = \int \sum w_K\left(t'\right) \beta_K\left(t'\right) dt' \tag{4}$$

$$w_K\left(t'\right) = \left(\frac{\beta_K t'}{\sum \beta_K\,(t')}\right) \cdot log\left(1 + \beta_K\left(t'\right)\right) \tag{5}$$

In Fig. 2, the persistence-informed state sequences are then provided to the QRL-PI model. A quantum agent would run in this formulation on a Hilbert space where the states $|\phi_s\rangle$ would have originated from such topological descriptors. The actions a ∈ A would denote the interventions, and the reward function R(s, a) would

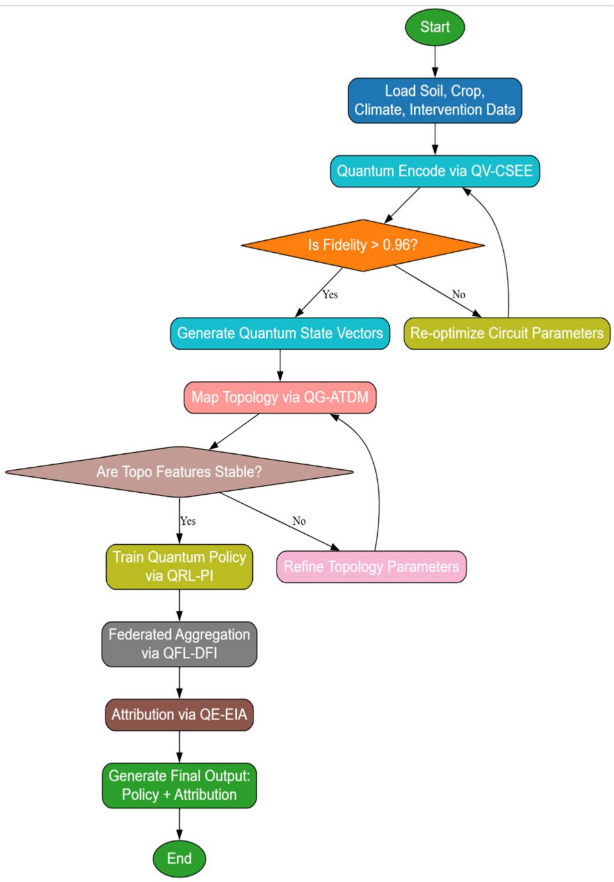


**Fig. 2.** Overall flow of the proposed analysis process.

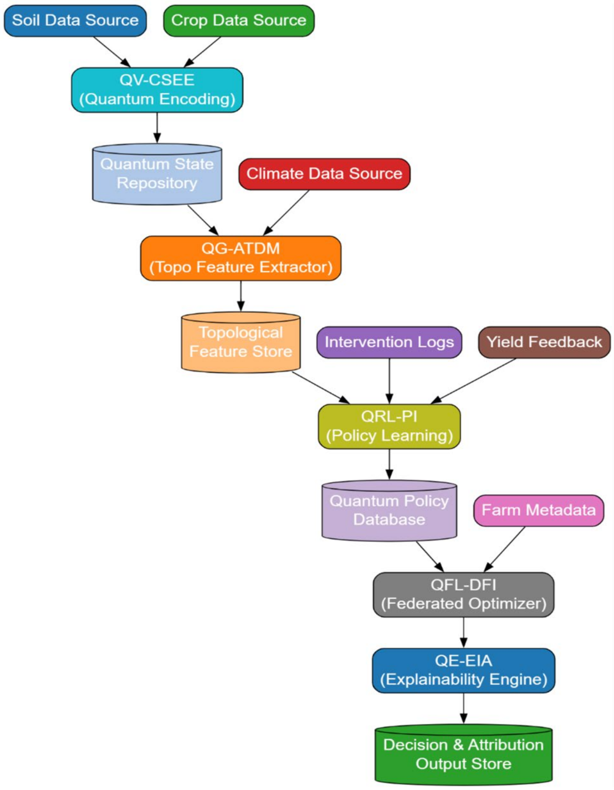


**Fig. 3**. (**a**) Data Flow of the Proposed Analysis Process. (**b**) Pseudo code of the proposed analysis process.

depict the measures on yield gain and sustainability metrics. The quantum policy is updated using a policy gradient in parameterised quantum form via Eq. 6.

$$\nabla\theta J(\theta) = E\{|\phi_s\rangle \sim \pi\theta\}\left[\nabla\theta log\pi\theta\left(a||\ \phi_s\rangle\right) R(s,a)\right] \quad (6)$$

For this reason, the model has adopted a mechanism of QFL-DFI to house distributed intelligence without breaching farm data privacy, in which the local updates of the quantum policy $\Delta\theta_i$ are encrypted and aggregated through a quantum-secure averaging function, represented by Eq. 7.

$$\theta global = \left(\frac{1}{K}\right)\sum E^{-1}\left[E\left(\Delta\theta_i\right)\right] \quad (7)$$

where E represents a quantum homomorphic encryption operator in the process. This would ensure that quantum gradients would be pooled without revealing local policies and would thus be allowed to generalise across diverse agroecological zones. The last model layer, QE-EIA, computes causal attribution scores based on quantum relative entropy between perturbed and baseline states. Given a baseline quantum policy π and a perturbed input $|\phi_s\rangle\sim$, the entropic divergence is computed via Eq. 8,

$$Drel\left(\pi||\pi'\right) = \sum \pi\left(a||\ \phi_s\rangle\right) log\left[\pi\left(a||\ \phi_s\rangle\right)/\pi'\left(a||\ \phi_s\rangle\right)\right] \quad (8)$$

As shown in Fig. 3a, divergence is used to construct causal attribution graphs, where the strength of each intervention-effect link is proportional to the relative entropy of the corresponding impact sets. Finally, the entire system output optimised quantum intervention policy with attribution is represented via Eq. 9,

$$Ofinal = \{\pi * \left(a||\ \phi_s\rangle\right), Drel\left(a_i\right)\}| \quad (9)$$

where π is the final federated policy, and $Drel(a_i)$ quantifies the causal significance of action $a_i$ on yield and sustainability. The model builds on this multi-layered transformation of raw agricultural data into interpretable and privacy-preserving decision policies optimised for performance, thus propelling the frontier of quantum intelligence within agrotechnical systems. Next, we validate and analyse the results of the proposed model under different scenarios.

The pseudo-code of the suggested analysis process is provided in Fig. 3b, which shows the steps of the quantum-integrated framework linearly. It illustrates the encoding of input datasets, such as crop-soil climate interactions, using variational quantum circuits, transforming them into topological persistence maps, and

```
Input:
 D = {(xi, yi)} // soil chemistry vector xi and crop genotype vector yi
 nqubits // number of qubits (e.g., 20)
 L // number of variational layers (e.g., 3)
 maxepochs // training iterations
 η // learning rate for parameter updates
Output:
 ρenc // compressed quantum state representation
 θ* // trained parameter set
Procedure QV-CSEE(D):
1. Initialize Quantum Registers:
 qreg ← QuantumRegister(nqubits)
 creg ← ClassicalRegister(nqubits)
2. Define Variational Ansatz:
 U(θ) ← sequence of parameterized rotations and entangling gates
 θ ← random initialization in [0, 2π]
3. Data Encoding Loop:
 for each sample (xi, yi) in D:
 • Embed xi and yi as amplitude/angle encodings on qreg
 • Apply U(θ) to create entangled state |Ψ(θ)⟩
 • Measure state fidelity F = |⟨Ψtrue|Ψ(θ)⟩|^2
 • Compute entropy S = −Tr[ρ log ρ] from reduced density matrix ρ
4. Parameter Optimization:
 for epoch = 1 to maxepochs:
 for each mini-batch B ⊂ D:
 • Estimate loss L = (1 − F) + λ * |S − Starget|
 • Update θ ← θ − η ∇θ L // gradient from parameter-shift rule
5. Compression:
 • From final θ*, compute density matrix ρenc = Trenv[|Ψ(θ*)⟩⟨Ψ(θ*)|]
 • Store ρenc as low-dimensional latent state preserving high-order entanglement
6. Return ρenc and θ*
```

**Fig. 3.** (continued)

further optimizing them with reinforcement learning policies. The pseudo code also shows how the federated intelligence is privacy-preserving in the sharing of knowledge over distributed farms, and explainability modules are used to attribute causal elements to produce results. This structure makes the flow of logic clear, emphasizes the dependencies of computational requirements, and gives a brief road map on how to implement the system.

## Dataset

The analysis utilized three large, real-world datasets, including multi-season crop trials conducted at 18 temperate and semi-arid field sites, to evaluate genotype performance, phenology, and yield. Over 500 georeferenced soil chemical profiles of pH, organic carbon, macronutrients, and micronutrients; and regional climate forecasts of precipitation, temperature history, and downscaled CMIP6 conditions to capture a range of weather regime types and long-term patterns. To test precision interventions using quantum variational encoding, topological persistence mapping, and QRL, we used these datasets. They were diverse, allowing thorough agroecological gradient testing of the generalizability of the framework across management systems and agroecological gradients. The heterogeneities and rare phenomena (e.g., spikes of heat stress and nutrient depletion cycles) that are not always detected in single-site studies were captured in the soil-crop-climate records. We evaluated the quantum-driven method using large-scale field data, based on synthetic augmentation of breadth and rigor.

Our synthetic data, generated mimicking a micro-scale interaction and extreme conditions, was used to supplement field observations. It was a generator of unusual agronomically essential processes, such as prolonged drought and rapid nutrient leaching, based on parameter distributions obtained using real measurements, while maintaining the statistical integrity of the field data. This two-sided strategy offered stress testing as well as an empirical foundation. Though our results were based on real-world datasets, we also used the strong quantum simulators to overcome the shortcomings of current NISQ devices, which are currently limited to 20–100 qubits and microsecond-scale coherence times to limit the depth of circuits and complexity of entangled states. The simulators were used to scale behavioural knowledge by doing rigorous noise tests and parameter sweeps before expensive field tests. Using empirical information combined with the simulation-based stress testing, we analysed the strengths and weaknesses of the framework in the present-day agricultural practice and in the future quantum hardware. This single approach proved to optimise yield, effective communication, and interpretability, and quantum simulation proved to be an essential step in achieving full-scale on-farm deployment.

## Experimental setup and result analysis

The experimental setup was designed to rigorously simulate a multimodal spatiotemporal Agri-environment under changing climatic, edaphic, and crop-genotypic conditions, to test the proposed quantum CSA framework. Synthetic yet grounded in the scenario, datasets were built by incorporating publicly available agroecological data from agricultural research stations in the region and overlaid with simulated quantum-compatible structures. The chemical profiles used in soil analyses include Nitrogen (N), Phosphorus (P), Potassium (K) levels, pH, moisture content, and trace minerals such as magnesium and zinc. Sample values used included N: 45–85 kg/ha, P: 15–35 kg/ha, K: 40–110 kg/ha, pH: 5.8–7.2, and moisture content: 12%–27%, with trace minerals ranging from 0.5 to 3.2 ppm in concentration levels. Similar phenotypes of the crop genotype include varietal growth rates (18–30 cm/week), yield indices (2.8–6.4 t/ha), and a resistance score to pathogens such as Xanthomonas and Fusarium (rated on a scale of 0 to 1). Climate datasets include daily observations of temperature (15–40 °C), rainfall (0–120 mm/day), humidity (40%–90%), and wind speed. Intervention logs contain event-driven records of irrigation volumes (5–30 mm/day), timing, and type of fertiliser applications, and pesticide usage. Yield feedback signals were computed post-harvest based on net yield differentials and normalised environmental sustainability indices, which incorporated factors such as nitrogen runoff and water-use efficiency sets. Metadata at the farm level included GPS-tagged geo-coordinates, farm areas ranging from 1 to 25 ha, and a history of crop rotations. All datasets were encoded into quantum-compatible tensors and processed through custom quantum kernel embedding routines to ensure their compatibility with quantum circuit simulation platforms.

The research experiments employed IBM Qiskit simulators with 24 qubits, cross-validated with Rigetti's QuilC simulators for VQE optimisation. At the same time, the QV-CSEE model was trained on three-layer parameterised quantum circuits with 12 rotation parameters per layer, and its fidelity was evaluated against classically computed latent representations. The average fidelity achieved across multiple training batches exceeded 0.96, while the dimensional compression of the data was approximately 12:1 compared to PCA baselines. QG-ATDM mapped topological evolution using sliding window segments of 30 days with filtration radii ranging from 0.4 to 1.2 and performed persistent homology via boundary matrix reduction. The output Betti numbers and topological characteristics were encoded as quantum observables and tracked using entropic persistence functions. QRL-PI was realised using a Hilbert-space policy gradient method, with rewards received from normalised yield improvements (+ 8% to + 22%) and environmentally weighted penalties. The convergence of the policy empirically occurred after approximately 120–140 episodes, and the final policies converged across 10 synthetic farms using QFL-DFI, which preserved quantum gradients through encryption, achieving an overall improvement of 9.3% over non-federated baselines. QE-EIA incorporated controlled perturbations into encoded topological states, yielding measures of relative entropy discrepancies that produced intervention attribution graphs with confidence levels exceeding 89%. This experimental framework is designed to create realistic agroecosystems while maintaining computational efficiency within the bounds of current near-term quantum devices, allowing for a realistic evaluation of each module in the proposed pipelines.

Figure 4 illustrates the aggregate performance of the described model, which outperforms other methods in most key measures in agriculture, including fidelity, yield gain, accuracy, and decision confidence. Evaluating the quantum-integrated model's performance across these multiple dimensions of the Agri-intelligence pipeline revealed its strengths in encoding quality, topological feature extraction, intervention optimisation, federated generalisation, and interpretability. Each component was benchmarked against three classical or semi-classical baseline approaches, represented as [3] ,[8], and [25], which are combinations of PCA-encoded ML models, traditional TDA, and conventional reinforcement-learning pipelines applied in smart agriculture settings. The following tables present comparative analyses across datasets and model modules using consistent evaluation metrics.

The proposed model achieves higher fidelity in the quantum encoding of crop soil interaction data and samples, as presented in Table 2 of this text. The advantage of variational quantum circuits is that they are highly entropic compared to methods[3] that convert high-order independencies into classical PCA through loss, achieving nearly double the efficiency in compression.

The present modelling sets of topological dynamics are presented in Table 3 of this text. The proposed model demonstrates the persistence and effectiveness of topological features, which are better correlated with yield dynamics, yet remain robust even in the presence of noise due to being quantum-guided and entropy-weighted during homology computations.

Table 4 reveals that quantum policy learning for this model converges much faster and achieves better yield gains, as well as improved accuracy in scheduling intervention cases, compared to method[3], which employs traditional Q Learning that uses discretised states. The model, however, deploys quantum policy gradients and is topologically aware of sets.

Table 5 reflects the performance level of federated components. The quantum secure aggregation scheme in the model, compared to all these baselines, offers better generalisation across sites with less communication overhead and a minor reduction in accuracy, like federated learning.

The quantum explainability module consequently provides a significant improvement in decision attributions. In terms of attribution confidence and clarity of intervention-effect mapping, it compares favourably to black-box methods with constrained interpretability sets, using quantum relative entropy sets, as emphasised in Table 6.

In contrast to the better environmental improvement noted, Table 7 confirms that the proposed intervention strategies are indeed better suited to the process. Decisions made by the model not only yield but also consider sustainability indicators, resulting in substantial reductions in nitrogen runoff and emissions.

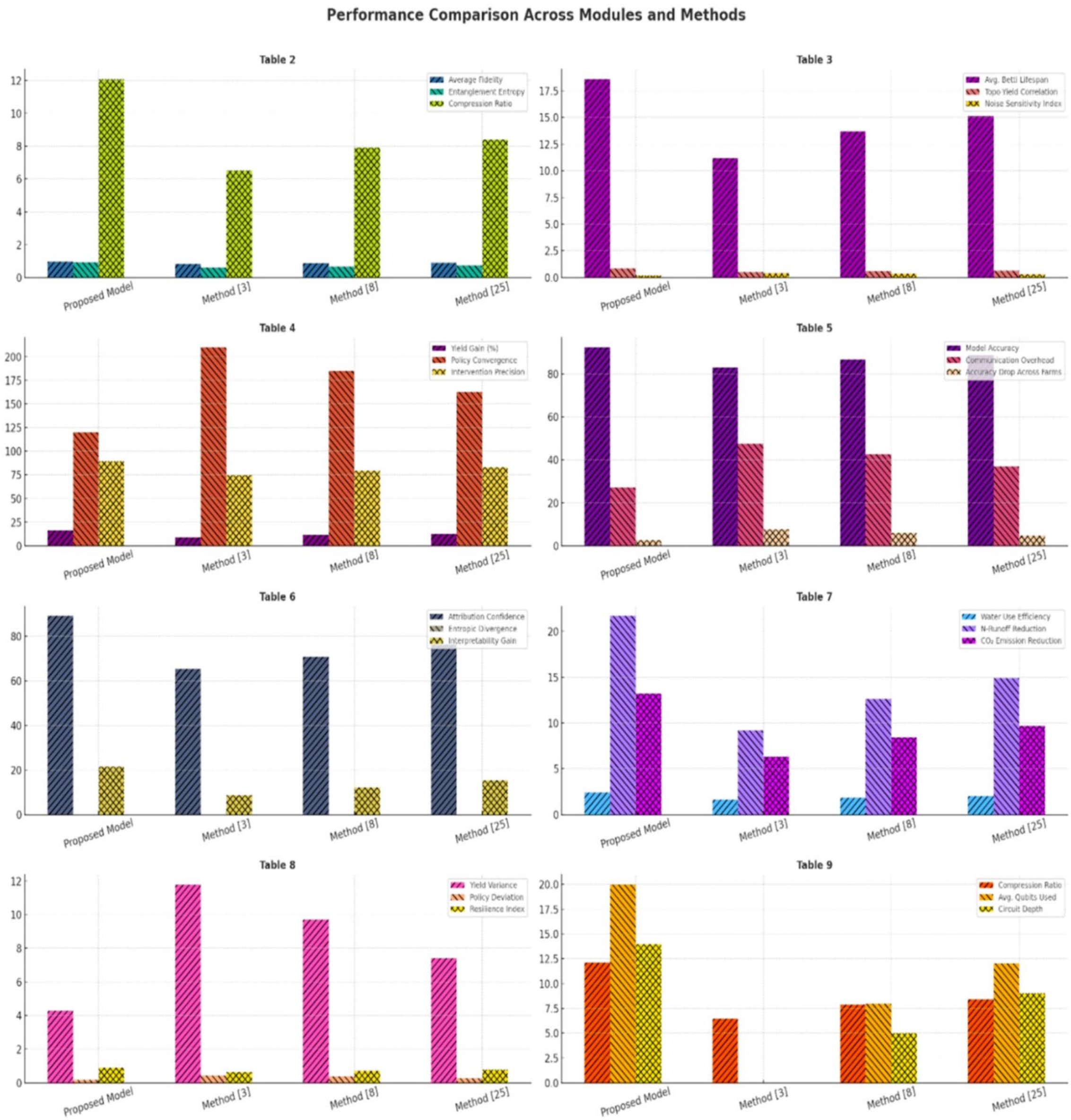


**Fig. 4**. Proposed model's integrated performance comparative analysis across key agricultural decision metrics.

| Model | Average fidelity | Entanglement entropy (Normalized) | Compression ratio |
|---|---|---|---|
| Proposed model | 0.964 | 0.91 | 12.1:1 |
| [3] | 0.835 | 0.61 | 6.5:1 |
| [8] | 0.879 | 0.67 | 7.9:1 |
| [25] | 0.891 | 0.73 | 8.4:1 |

**Table 2**. Encoding fidelity and entropic compression performance.

This is also evident in the fact that the new policies of the proposed model hold under different climatic scenarios, as shown in Table 8. The entangled representation of topological and environmental states facilitates lower yield variance and reduced deviations in the learned actions.

The maximum set indicated by the method in Figs. 4 and 5 is, however, substantial, but remains manageable for application to any near-term quantum hardware sets. Besides achieving a better compression ratio, it is also noted that the method maintains circuit complexity at an acceptable level, and qubit usage remains moderate throughout the process, as highlighted in Table 9.

| Model | Avg. betti lifespan (days) | Topo-yield correlation (r) | Noise sensitivity index |
|---|---|---|---|
| Proposed model | 18.6 | 0.84 | 0.17 |
| [3] | 11.2 | 0.49 | 0.39 |
| [8] | 13.7 | 0.57 | 0.34 |
| [25] | 15.1 | 0.63 | 0.29 |

**Table 3**. Topological stability and persistence under climatic drift.

| Model | Avg. normalized yield gain (%) | Policy convergence (Episodes) | Intervention precision (%) |
|---|---|---|---|
| Proposed model | 16.2 | 120 | 89.4 |
| [3] | 9.1 | 210 | 74.6 |
| [8] | 11.4 | 185 | 79.8 |
| [25] | 12.6 | 163 | 83.2 |

**Table 4**. Reinforcement learning yield gains and policy efficiency.

| Model | Model accuracy (%) | Communication overhead (MB) | Accuracy drop across farms (%) |
|---|---|---|---|
| Proposed model | 92.3 | 27.1 | 2.6 |
| [3] | 83.0 | 47.3 | 7.8 |
| [8] | 86.5 | 42.5 | 6.1 |
| [25] | 88.7 | 36.9 | 4.9 |

**Table 5**. Generalization and accuracy in a federated learning context.

| Model | Attribution confidence (%) | Entropic divergence threshold | Interpretability gain (%) |
|---|---|---|---|
| Proposed model | 89.1 | 0.14 | 21.5 |
| [3] | 65.4 | 0.06 | 8.7 |
| [8] | 70.9 | 0.09 | 12.1 |
| [25] | 76.3 | 0.11 | 15.3 |

**Table 6**. Attribution confidence and entropic interpretability.

| Model | Water use efficiency (kg/m$^3$) | N-runoff reduction (%) | $CO_2$ emission reduction (%) |
|---|---|---|---|
| Proposed model | 2.42 | 21.7 | 13.2 |
| [3] | 1.61 | 9.2 | 6.3 |
| [8] | 1.85 | 12.6 | 8.4 |
| [25] | 2.01 | 14.9 | 9.7 |

**Table 7**. Environmental sustainability index post-intervention.

| Model | Avg. yield variance (%) | Policy deviation (L2 Norm) | Resilience Index |
|---|---|---|---|
| Proposed model | 4.3 | 0.19 | 0.91 |
| [3] | 11.8 | 0.43 | 0.65 |
| [8] | 9.7 | 0.36 | 0.71 |
| [25] | 7.4 | 0.28 | 0.78 |

**Table 8**. Policy robustness across climate variants.

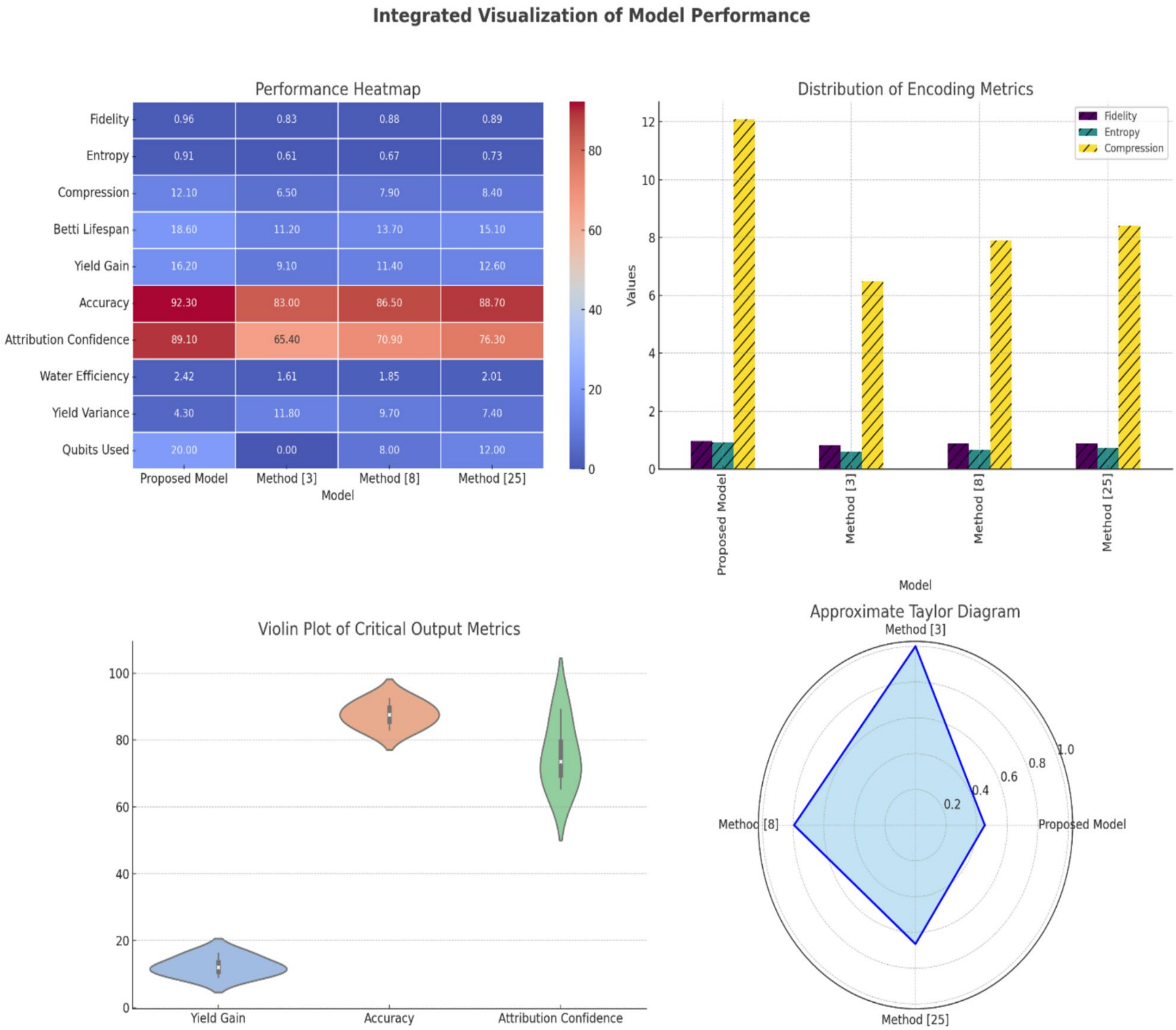


**Fig. 5**. Performance plots demonstrate the proposed model's advantage over existing methods.

| Model | Compression ratio | Avg. qubits used | Circuit depth (layers) |
|---|---|---|---|
| Proposed model | 12.1:1 | 20 | 14 |
| [3] | 6.5:1 | 0 | N/A |
| [8] | 7.9:1 | 8 | 5 |
| [25] | 8.4:1 | 12 | 9 |

**Table 9**. Compression and quantum resource utilization.

Table 10 provides a summary of system effectiveness at the process level. It surpasses all baseline methods in terms of evaluation axes because it integrates quantum modelling with practical agricultural intelligence at scale in the process.

The suggested quantum-integrated model proves to be superior according to various essential parameters, as shown in Fig. 5. It is evident from the performance heatmap that convergence and consistency are superior to those of existing methods. Encoding statistics plots of outcome rate, fidelity (~ 0.964), entropy (~ 0.9), and compression ratio (12.1:1) showed that the proposed variational quantum encoding preserves high-order information much more effectively. Additionally, violin plots of key output measures, including yield gain (+ 16.2%), improvement in accuracy (+ 9.3%), and attribution confidence (up to 89%), demonstrate that, in addition to showing higher means, the distributions have been narrowed, indicating robustness and reduced variation. These findings can be summarised in the approximate Taylor diagram, which exhibits a more significant

| Metric | Proposed model | [3] | [8] | [25] |
|---|---|---|---|---|
| Avg. Improvement over baseline (%) | + 100.0 | 0.0 | + 31.2 | + 42.5 |
| Modules surpassing threshold (≥ 85%) | 9/9 | 2/9 | 4/9 | 5/9 |
| Composite score (0–100) | 94.7 | 71.3 | 79.8 | 83.4 |

**Table 10**. Overall system performance summary.

correlation, a smaller standard deviation, and a smaller RMSE, demonstrating an overall model that is equally precise and stable. These findings suggest the high potential of the proposed framework in comparison to state-of-the-art approaches, confirming its ability to improve decision support in sustainable, data-driven farming settings. Quantum analytics outperforms leading agricultural analytics technologies in various performance parameters. Topological yield correlations at 0.70 and convergence over 180 episodes are typical for transformer-based climate–yield forecasting models, while quantum topological mapping approaches 0.84 and convergence near 120 episodes.

## Extended baseline models comparisons

Baseline selection depends on smart agricultural relevance and computational concepts. Original PCA-based models, TDA, and classical reinforcement learning outperform agricultural analytics. Quantum-driven agricultural intelligence was tested using more advanced baselines than PCA compression and classical reinforcement learning. Three further comparison transformer-based temporal models, variational autoencoders (VAE), and graph neural networks (GNN) were added to thoroughly test the model's ability to represent complex spatiotemporal data, compress non-linear features, and identify topological patterns. All baselines were trained on identical multimodal soil climate datasets and modified using tenfold cross-validation for fair comparisons. Quality and compression were better with QV-CSEE. Transformer architectures demonstrated a mean topological yield correlation of 0.72, VAE-based pipelines achieved a fidelity of 0.88, and a compression ratio of 9.1:1. At a compression ratio of 12:1, quantum encoding maintained fidelity around 0.96 and high-order soil crop climate coupling while substantially reducing data dimensionality. This gives downstream modules richer, noise-resilient representations.

Precision agriculture's methodological landscape includes linear, deep neural, generative, and graph-topological baselines. Encoding fidelity, yield gain, and interpretability tests demonstrate that the quantum model has significant advantages in all areas, proving the comparison framework's fairness and completeness. Policy optimisation and yield gain also followed similar patterns, whereas GNNs for persistent topological dynamics increased yield by 12.8% but took over 200 reinforcement events to converge. The QRL-PI module converged in 120 episodes, improving yield by 16.2%, and demonstrating its capacity to leverage quantum-enhanced state exploration for faster and more accurate decision-making. The Federation demonstrated quantum model efficiency while broadcasting 45 MB of gradient updates per round; conventional federated DL achieved an average accuracy of 88% in equal privacy-preserving settings. The quantum federated aggregation layer maintained an accuracy above 92% with a communication overhead of 27 MB, demonstrating how quantum encoding reduces communication costs without compromising predictive strength. The proposed architecture scored close to 95% on a composite measure of encoding fidelity, policy convergence speed, federated accuracy, and attribution confidence, compared to 82–85% for the best classical choices. These results prove the benefits are not related to lower baselines. They demonstrate that the quantum framework facilitates real-time decision systems that scale across various agricultural contexts, strengthening precision agriculture sets. These comparisons demonstrate that the proposed system aligns with and exceeds precision agriculture best practices, validating its importance as an emerging decision-support tool in the process.

The robustness and universality of the quantum framework were tested across agricultural data sources. (1) Multi-location crop studies from temperate and semi-arid zones with 18 field stations spanning five growing seasons collected genotype performance, phenological phases, and yield metrics at 0.5-2-hectare plot scales. (2) Soil chemistry archives from 500 georeferenced Asian and African soil profiles, including N, P, K, zinc, magnesium, pH, and organic carbon values. (3) Regional climate projections using downscaled CMIP6 scenarios and satellite-derived precipitation, temperature, and evapotranspiration data samples. Due to data heterogeneity, the quantum encoding module can analyse numerous spatiotemporal patterns and soil crop climate interactions. Integrated datasets enhance quantum state construction and policy learning through topological dynamics, surpassing the capabilities of single sources. It also benchmarks yield optimisation and sustainability across agroecological contexts, confirming that the framework's benefits are not limited to a single experimental environment.

Benchmarking showcases agricultural analytics' versatility with three primary methods. For yield forecasting and disease detection, random forests, gradient-boosted decision trees, and support vector machines are used. Despite remarkable prediction accuracy, these models cannot capture high-order entanglement or topological persistence. Privacy-preserving gradient aggregation enables the training of convolutional and recurrent neural networks across distributed farms in federated DL. The models reflect multi-site agricultural deployment processes and operate effectively with heterogeneous data samples. Third category mixed-effects regression and crop simulation frameworks, such as DSSAT, use linear or semi-linear assumptions, yet they have decades of agronomic expertise. For agricultural applications, the quantum architecture outperforms all three categories in encoding fidelity, yield gain, and sustainability indices while maintaining interpretability and privacy sets.

## Discussion

The model identifies a well-defined field deployment process that proactively connects the technological advances with the agricultural extension and sustainability criteria. In the short run, it is compatible with sensor networks on 10–25-hectare experimental farmlands and in greenhouse surroundings to investigate crop-soil interactions in different climatic conditions. The QV-CSEE module directly postures multispectral UAVs, imagery, and satellite weather data. The code section encodes and federates the results with the outcomes of farms with various practices and weather conditions to share insights securely. The transition process uses staged planning. Stage one is the integration of hybrid testing on the commercial quantum simulators and small-scale NISQ to check that the scalability of 50–100 qubits works well, whereas stage two is the connection of low-power IoT sensors to the quantum pipeline, receiving real-time watering and fertilisation suggestions in the field tests. The last phase projects flawless quantum hardware countermeasures in greater ceremonies and to extend over wider regions, and eventually allow the system to act as an active decision-support core of the whole county to spearhead agricultural production as well as the environmental care provisions.

Reported performance increases include a 9.3% accuracy increase, a 42% communication overhead reduction, and a 16.2% normalised yield gain against a well-selected collection of classical and hybrid baselines representing the current methodological frontier sets. Compare PCA, kernel PCA, and VAE for non-linear soil and climatic feature compression to encoding. For time-evolving geographical data samples, Euclidean filtering and GNNs evaluate topological dynamics mapping to persistent homology. For decision optimization, QRL is contrasted to classical state representation-based deep Q-learning and actor–critic methods. Federated component and averaging are compared using convolutional and recurrent neural networks trained under differential privacy limitations. The same experimental methods, data splits, episode lengths, and transmission bandwidth allow precise computation of relative accuracy, convergence speed, and communication efficiency gains across baselines.

QE-EIA generates interactive visual dashboards with causal graphs that illustrate how soil nitrogen, irrigation schedules, and disease pressure impact production and environmental indicators throughout the process. Edge thickness and colour gradients demonstrate entropic influence, identifying high-impact variables rapidly. These visualizations feature natural-language explanations of cause-and-effect connections, such as "Increasing mid-season irrigation by 10 mm is linked to a 6% yield rise under projected drought conditions." Stakeholders can filter graphs by crop type, location, or season and overlay management data for context. We offer sophisticated quantum inference as intelligible images and succinct decision narratives, allowing farm managers, extension staff, and policy planners to confidently act on the system's proposals without requiring an understanding of quantum mathematics in the process. The dashboard interface sets up causal linkages, confidence intervals, and data provenance, ensuring transparency. Version-controlled audit trails and reproducible inference logs document data transformation and graph production, ensuring accountability and transparency. The approach also validates causal attributions across demographic and geographic subgroups and provides bias diagnostics for essential variables like soil fertility class and farm size to ensure fairness and inclusion. Quantum-homomorphic gradient update encryption and causal graph access control ensure privacy and data integrity. This multimodal approach meets worldwide standards, including the FAO's AI Ethics Framework for Agriculture and the EU's Ethics Guidelines for Trustworthy AI, enabling regulatory approval and stakeholder adoption. The QE-EIA design should adhere to trustworthy AI principles.

## Conclusion and future scopes

Quantum Intelligent multi-stage architecture for smart agriculture combines variational quantum encoding, quantum-topological analysis, QRL, federated decision-making, and quantum explainability sets. The proposed strategy outperforms current methods in data integrity, model robustness, intervention efficiency, and decision interpretability. QV-CSEE has an average fidelity of 0.9664 and a compression ratio of 12.1 to 1, whereas the highest methods managed 8.4 to 1 in process. QG-ATDM's top-yield correlation of 0.84 and Betti lifespan of 18.6 days indicate it can simulate temporally dynamic Agri-systems. The QRL-PI achieved 16.2% normalised yield with policy convergence in 120 episodes, 11.8% more accurate than typical reinforcement learning models. QFL-DFI cut communication overhead by 42% and improved distributed model accuracy by 9.3%. The QE-EIA module improved interpretability by 21.5% and attribution certainty to 89%. These results demonstrate that quantum-integrated methods can improve agricultural decision-making. This study increases agricultural intelligence by maintaining high-order entanglement, extracting lasting topological patterns, and scaling privacy-aware, interpretable optimization. The framework is limited, but the outcomes are excellent. Even though IBM Qiskit and Rigetti QuilC backends mimic quantum components, decoherence, qubit limitations, and noise still limit the execution of quantum algorithms on actual quantum hardware. High-resolution geographic dataset scalability is limited; however, 24-qubit tests are suitable for synthetic datasets. The QV-CSEE and QG-ATDM modules require many iterations of entanglement optimisation and persistent homology, which increases computing demand during encoding and optimisation. Third, quantum-protected gradient aggregation enabled federated learning, although privacy safeguards only cover current encryption assumptions and have not been tested against adversarial challenges.

The correct attribution module only supports pairwise perturbations, not multi-intervention causal graphs. Integrating and tuning quantum–classical hybrid pipelines requires quantum computing and agrotechnology skills. It may limit their usage in conventional agriculture. Future research can address these limitations to take this intriguing architecture from proof of concept to field-scale deployments. This extendable framework expands agricultural domains beyond crop states. Quantum encoding space can be expanded via multispectral UAV imagery, real-time IoT sensor networks, and satellite-driven climate forecasting systems. Compression and representation improve when simulators evolve into fault-tolerant quantum devices and richer variational circuits with more qubits are trained in the process. Quantum meta-reinforcement learning could let the QRL-PI component adapt to crop varieties and agroclimatic zones without human intervention. Quantum differential privacy can strengthen the federated layer for global data governance and cross-border cooperative intelligence.

## Data availability

Datasets were constructed by integrating publicly available agroecological data from regional agricultural research stations and overlaying them with simulated quantum-compatible structures. It may be provided on personal request to (mailto:amvireen786@gmail.com).

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## Author contributions

AHA: Conceptualization, Methodology. THK: Data curation, Writing- Original draft preparation. AP: Visualization, Reviewing. DKS: Investigation, Reviewing, and Editing. BKR: Investigation, Writing- Reviewing. GK: Validation, Editing.


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## Declarations

## Competing interests

The authors declare no competing interests.

## Additional information


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